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Aggregated demand response modelling for future grid scenarios

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ABSTRACT

With the increased penetration of intermittent renewable energy sources (RESs) in future grids (FGs), balancing between supply and demand will become more dependent on demand response (DR) and energy storage. Thus, FG feasibility studies will need to consider DR for modelling net future demand. This paper proposes a generic demand model which represents the aggregated effect of DR in terms of a simplified market model of a FG. The model is based on a unit commitment problem aiming to minimise the system cost, and is intended specifically for modelling net demand by including the effect of DR in FG scenario studies. However, the model does not presume any particular market structure. As such, it is not suitable for modelling of existing electricity markets, but rather its aim is to capture the behaviour of future electricity markets provided a suitable market structure is adopted. The conventional demand model in the optimisation formulation is augmented by including the aggregated effect of numerous users equipped with rooftop photovoltaic (PV)-battery systems at higher voltage levels, without explicitly modelling the distribution level. In the model, the users are aiming to maximise self-consumption and are assumed to be *price anticipators*. As a case study, the effect of the demand model is studied on the load profile, balancing and loadability of the Australian National Electricity Market in 2020 with the increased penetration of RESs. The results are compared with the demand model in which users are assumed to be *price takers*.

1. Introduction

The increased penetration of renewable energy sources (RESs) in future grids (FGs) will create significant challenges for balancing, stability and security. FG feasibility studies have demonstrated that relying on high penetration of diverse RESs is possible assuming enough flexible generation and/or utility storage are available to keep the network in balance [1–10]. A preliminary study by the University of Melbourne Energy Research Institute has proposed a zero-carbon electrical grid for Australia in 2020 [1]. The University of New South Wales researchers have analysed the viability of 100% RES scenarios considering a copper plate model for the Australian National Electricity Market (NEM) [2,3]. They have suggested 100% RESs electricity in the NEM, at the current reliability standard, would be technologically feasible. Also, the least-cost mix of 100% RESs scenario has been determined for the future of the NEM. Similarly, the least-cost mix of high penetration of diverse RESs and conventional generation has been determined for the future of the PJM, California and New Zealand networks in [4–6], respectively.

However, these studies have only focused on simple balancing by using a simplified grid model such as the copper plate model. On the other hand, the penetration of distributed generation (DG) has been increasing significantly in recent years, and greater penetration of small-scale battery storage is anticipated in power systems [11–17]. In particular, global installed capacity of rooftop photovoltaic (PV) has increased from approximately 4 GW in 2003 to nearly 128 GW in 2013 mainly due to electricity price increases, government incentives and also worldwide drop of PV capital cost [11,12]. In Australia, installed capacity of rooftop PV (which is mostly installed by residential and commercial customers) has grown from approximately 0.8 GW in 2011 to over 4 GW in 2014 [14]. Recent studies have demonstrated that users equipped with PV-battery systems will reach retail price parity in the foreseeable future in the USA grids and the NEM [11–13]. In light of these developments, a question arises how to model the aggregated net demand (including DG, storage and demand response (DR)) to study FG scenarios.

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Nomenclature

Parameters

$g \in G$	Supplier g and set of G suppliers.
$m \in M$	Load aggregator m and set of M load aggregators.
$h \in H$	Time slot h and set of H slots in the horizon.
$i \in N$	Node i in the system and set of N Nodes.
$r_i \in R$	Region i in the system and set of R regions.
i, j	Indices.
α, β	Incremental changes for $P_{\mathrm{B,cha}}^{\max,m}$ and $E_{\mathrm{loss}}^{\mathrm{B},m}$ calculation.
Δh	Time step interval.
$\tilde{h}$	Time index.
$P_g^{\max}$	Maximum power limit of supplier g.
$P_g^{\min}$	Minimum power limit of supplier g.
RU_g	Ramp-up rate of supplier g.
RD_g	Ramp-down rate of supplier g.
MUT_g	Minimum up time interval of supplier g.
MDT_g	Minimum down time interval of supplier g.
$P_{\mathrm{F}}^{\max,m}$	Maximum flexible power demand limit of aggregator m.
$P_{\mathrm{F}}^{\min,m}$	Minimum flexible power demand limit of aggregator m.
$B_{\mathrm{SOC}}^{\max,m}$	Maximum battery storage state of charge (SOC) limit of price-responsive users communicating with aggregator m.
$B_{\mathrm{SOC}}^{\min,m}$	Minimum battery storage SOC limit of price-responsive users communicating with aggregator m.
$P_{i,j}^{\max,\mathrm{L}}$	Maximum line power limit from node i to node j.
$P_{i,j}^{\min,\mathrm{L}}$	Minimum line power limit from node i to node j.
$B_{i,j}$	Susceptance of line between node i and node j.

Variables

$s_g(h)$	Binary decision variable on on/off status of supplier g in slot h.
$u_g(h)$	Binary start-up decision variable of supplier g in slot h.
$d_g(h)$	Binary shut-down decision variable of supplier g in slot h.
$P_g(h)$	Generated active power by supplier g in slot h.
E^m	Total energy requirement of aggregator m over a horizon.
$P_{\mathrm{F}}^m(h)$	Aggregated flexible power demand of aggregator m in slot h.
$P_{\mathrm{L}}^m(h)$	Aggregated inflexible power demand of aggregator m in slot h.
$P_{\mathrm{U}}^m(h)$	Aggregated power demand of price-responsive users communicating with aggregator m before utilising newer demand-side technologies in slot h.
$P_{\mathrm{PV}}^m(h)$	Aggregated PV generation of price-responsive users communicating with aggregator m in slot h.
$P_{\mathrm{LF}}^m(h)$	Aggregated net demand of aggregator m in slot h.
$P_{\mathrm{res}}(h)$	Required reserves in slot h to maintain mismatches and system stability.
$P_{\mathrm{B}}^m(h)$	Battery storage power for aggregator m in slot h.
$P_{\mathrm{B,cha}}^{\max,m}$	Maximum battery charging rate for aggregator m. This is a limiting variable to ensure that the total storage capacity is not exceeded.
$B_{\mathrm{SOC}}^m(h)$	Battery storage SOC of price-responsive users communicating with aggregator m in slot h.
$E_{\mathrm{loss}}^{\mathrm{B},m}$	Total battery energy loss of price-responsive users communicating with aggregator m over a horizon.
$P_{i,j}^{\mathrm{L}}(h)$	Transferred power by line from node i to node j in slot h.
$P_{i,j}^{\mathrm{loss,L}}(h)$	Power loss of line between node i and node j in slot h.
$\delta_i(h)$	Voltage angle at node i in slot h.

Functions

$C_g^{\mathrm{fix}}(.)$	Fix cost of supplier g.
$C_g^{\mathrm{su}}(.)$	Start-up cost of supplier g.
$C_g^{\mathrm{sd}}(.)$	Shut-down cost of supplier g.
$C_g^{\mathrm{var}}(.)$	Variable cost of supplier g.
$\rho_g(.)$	Bid of supplier g for generating P_g.

While the effect of DR is neglected in most of the existing FG feasibility studies [1–5], it is considered in few studies mainly through two different ways:

Implicit modelling: DR is considered implicitly, but it is not reflected into the loads. For instance in [6], the effect of DR is considered through improving the capacity credit value for intermittent RESs (i.e. intermittency of RESs is decreased). However, due to the significant effect of loads on performance and stability of power systems, it can be expected that incorporating DR explicitly into the load models will affect the results of FG feasibility studies significantly.

Explicit modelling: In some recent studies [17–22], the aggregated effect of DR is reflected into the conventional demand models. Most of those studies [19–22], have aimed at including the effect of DR into the conventional demand models assuming existing market structures. Including the effect of DR into the demand models requires allowing for the interaction between demand and supply sides in some ways. This is mainly done through three different approaches. First, in some studies, the supply-side is modelled physically while price-responsive users are not represented physically [19,20]. In [19], the effect of flexible loads is analysed on reserve markets. That study presumes the flexible load represented by a tank model. Also, the reserve market is too simplified and physical constraints of the electrical grids (e.g. line limits) are not considered. In [20], flexible demand is represented via a price-elasticity matrix. The elasticities are a measure of the change in demand in response to a change in the electricity price, and are typically obtained from the analysis of historical data. Second, there is another study that model demand-side technologies physically while the supply-side is represented through the electricity price profile [18]. That study assumes users to be price takers, i.e. the effect of user actions is not considered in the electricity price. This assumption is usually considered when the amount of information provided to each user is limited [23]. Third, in few recent studies, both demand-side technologies and supply-side are modelled physically [21,22]. This approach necessitates the need for integrated simulations in which both supply and demand sides are jointly optimised, which can provide more realistic results [21]. In [22], the aggregated charging management approaches for plug-in electrical vehicles (PEVs) is integrated into the market clearing process. The market process, however, is too simplified and physical constraints of the electrical grids are not considered. It is worth mentioning that the focus of the existing explicit DR models is often on scheduling/bidding strategies for particular emerging demand-side technologies, e.g. PV-battery systems [18], flexible loads [19], HVAC [20,21], and PEVs [22].

Although the above models have proven their merits for the existing market structures, a generic modelling framework is still required to model net demand by including the effect of emerging demand-side technologies for FG studies. A key feature